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1. Title page

**SPATIAL LEARNING AND COGNITIVE MAPPING:
A NEURAL NETWORK APPROACH**

Grant No F4920-94-1-0238

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Final Report

Period Covered 1 Jun 94- 31 Dec 95

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**SPATIAL LEARNING AND COGNITIVE MAPPING:
A NEURAL NETWORK APPROACH**

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2. Original Objectives

Initially, the aim of this project was to analyze in more detail the following aspects of the (a) cognitive mapping system and (b) the action system of models that perform spatial cognitive tasks.

Cognitive mapping system:

1. Place discrimination.

a. The cognitive mapping system will generate place representations whenever an unfamiliar spatial location is visited.

b. Place discrimination will include a more detailed description of the processes that relate landmark (object) recognition, the computation of visual angles of the recognized landmarks, the perception of directional (local) views of the environment, and, finally, the integration of different local views into place representations.

c. Place discrimination will be accomplished using extramaze or intramaze landmarks.

2. Place interconnection.

a. The cognitive map will represent not only adjacency, but also accessibility. This will allow the cognitive map to represent different environmental constraints, such as opaque and transparent walls, obstacles, etc.

b. The cognitive map will represent not only accessibility but also distance and direction between places.

3. Reward location:

a. The cognitive map represents the location of food in the maze.

Action system:

1. Decision making.

a. Instead of a fixed decision time, decision making rules will reflect a variable decision time as a function of the knowledge of the environment.

2. Response-selection rules.

a. Response-selection rules will replace VTE behavior and stimulus-approach rules when the maze is well learned.

b. Response-selection rules will be inhibited when the fast-time prediction associated with a given response changes in response to changes in the structure of the maze.

3. Environmental exploration.

a. Exploration of the environment during global cognitive mapping will be a function of the knowledge of the environment (curiosity).

4. Navigational dynamics. The model will describe acceleration, velocity, and position of the system as a function of time during spatial navigation.

3. Status of the effort

The unexpected early termination of the contract generated havoc among the personnel involved in the project. At the beginning of the project, we had a difficult time finding a postdoctoral student qualified for a job that requires knowledge of computer science, animal

behavior, and neurophysiology. Finally, we hired Dr. Peter Williams in January of 1995. Initially, I trained Dr. Williams in the intricacies of modelling animal behavior, and we wrote some programs. Almost as soon as he started, we received the notification that the grant would be terminated in June, and he started searching for another job.

We managed, however, to complete several of the original objectives of the project and even extended the enterprise to include the building of real robots that perform spatial learning and cognitive mapping.

4. Accomplishments/New Findings

1. Place discrimination.

The cognitive mapping system generates place representations whenever an unfamiliar spatial location is visited.

2. Response-selection rules.

a. Response-selection rules will replace VTE behavior and stimulus-approach rules when the maze is well learned. We developed a sofisticated model capable of generating alternative responses in the presence of different cues and of modulating the intensity of these responses according to the location of the animal in the maze. For instance, given three alternative paths (A, B, and C) and three alternative approach responses, the model is capable of learning to approach A in spatial location X, B in spatial location Y, and C in spatial location Z. Or given two different motivations (thirst and hunger), the model is capable of learning to approach a water source when thirsty and the food source when hungry performing the adequate response in each case.

3. Searching Behavior

One of the most important applications of spatial learning and cognitive mapping in searching behavior. In some cases the objective of a search behavior is to encounter and remove of all targets (Figure 1, Left Panel), in other cases the objective is to encounter and remove a group of selected targets to open a path between Start and Goal points (Figure 1, Right Panel).

In both cases, several factors are important in guiding searching behavior:

1. Item distribution: The targets can distributed (a) randomly (Figure 2, Panel A), (b) uniformly (Figure 2, Panel B), (c) in concentrated patches (Figure 2, Panel C), (d) in dispersed patched (Figure 2, Panel D), (e) with some spatial periodical probability.

2. Search strategies: Alternative searching strategies include (a) random walks (Figure 3, Panel A) , (b) straight line walks, (c) moving around the perimeter and inwards to a central point in the search area (Figure 3, Panel B), (d) moving slowly and turning when the hit rate is high in order to stay within the boundaries of the patch (Figure 3, Panel C).

3. Perceptual learning: The agent's ability to detect the targets improves as a function of recent encounters with similar items.

4. Social cooperation: Search behaviors might benefit from social cooperation because a group of agents searching for a concentrated patch is more likely to encounter the patch than individual agents. Once the patch is found, all agents assemble at the found patch (See Figure 3, Panel D). We have designed a model of animal communication that will be applied to

this task.

5. Spatial learning: Rate of success might be improved by learning about the spatial location of the patch. We have designed a model of spatial learning that defines the location of the targets. Figure 4 (Top panel) shows that the location of the goal (G) is learned using only the visual angles to the square and round landmarks and, therefore, generalization surface A presents minima at G and G'. After training, when the rat starts at S it reaches G, when the rat starts at S' it reaches the mirror image of G, G'. Figure 4 (Bottom Panel) shows that the location of the goal (G) is learned using both the visual angles to the square and round landmarks and the visual angles between the landmarks and, therefore, generalization surface A presents only one minimum at G. After training, when the rat starts either at S or S' it always reaches G.

3.1. Formal Models of Searching Behavior

We started studying formal models of searching behavior. The models analyze at a theoretical level strategies that optimize the search and maximize the rate of encountering the target. In general, models are defined by (a) the different tasks the agent can do simultaneously (searching or removing targets), (b) the probability of encountering a target in a patch, (c) the agents' ability to detect targets with increasing search velocity and increasing distance to the target.

Formal models of searching behavior are important to (a) analyze optimal behavior under different constraints (limited energy or limited time to encounter a given percentage of targets) and (b) evaluate the performance of alternative network designs.

3.2. Neural network models of search behavior

We are simulating models that (a) use alternative searching strategies, (b) have different detection capabilities, (c) include or exclude spatial learning, and (d) include or exclude social communication, in (e) environments with different target distributions,

We have started by designing different neural networks that control search behavior. These models search a simulated environment in which the targets are presented in a patch. A measure of the efficiency of the network is the rate of encounters with the targets (number of targets detected per unit of time).

So far, we have analyzed several problems:

1. We have compared different strategies against the simplest possible tactic, i.e., random walk. A very simple strategy that dramatically improves the efficiency of the search (in terms of time) is to make search speed a decreasing function of the rate of encounters (See Figure 5).

2. We have designed a network capable of describing patch density at different points in space in a manner that is independent of the velocity of the search. The network is able to find the boundaries of the patch and to stay within those boundaries.

3.3. Building and testing autonomous robots

Based on computer simulated results, we are building small autonomous robots controlled by the same neural networks used in the simulations. The robots are able to search for and approach a source of light according to the internal state of the agent. We have now one small,

inexpensive robots (see Figure 6) that we will use to test searching behavior in an experimental arena. The floor of the arena contains a set of targets (light bulbs) that can be distributed in alternative ways (see Figure 2) and can be "removed" (turn off) by the robot.

5. Personnel Supported

1. Nestor Schmajuk
2. Greg Gale (Graduate Student)
3. Columbia
4. Columbia
5. Peter Williams (Postdoctoral student)
6. Henry Walker (Technician)

6. Publications

BOOKS

1. Schmajuk, N.A. Animal Learning and Cognition: A neural network approach. Cambridge University Press. In press

*This book incorporates three chapters on spatial learning and cognitive mapping.

PAPERS PUBLISHED IN SCIENTIFIC JOURNALS

1. Schmajuk, N.A. Behavioral dynamics of escape and avoidance: A neural network approach. In From Animals to Animats 3, D. Cliff, P. Husbands, J-A Meyer, & S.W. Wilson (Eds.), pp. 118-127, Cambridge, MA: MIT Press, 1994.

2. Schmajuk, N.A. Review of Intelligent Behavior in Animals and Robots by D. McFarland and T. Bosser. The Quarterly review of Biology, 69, 429, 1994.

3. Schmajuk, N.A., and Blair, H.T. Time, space, and the hippocampus. In N.E. Spear, L.P. Spear, and M.Woodruff (Eds.), Neurobehavioral plasticity: Learning, development, and response to brain insult. Hillsdale, NJ: Erlbaum Associates, 1995.

*This article refers to hippocampal participation in spatial learning and cognitive mapping.

4. Schmajuk, N.A., Urry, D., and Zanutto, B.S. The frightening complexity of avoidance: An adaptive neural network. In J.E.R. Staddon and Clive Wynne (Eds.), Models of action. Hillsdale, NJ: Erlbaum Associates, in press.

5. Schmajuk, N.A. Conditioning. In M. Arbib (Ed.), The Handbook of brain theory and neural networks, Cambridge, MA: MIT Press, 1995.

6. Schmajuk, N.A. Cognitive Maps. In M. Arbib (Ed.), The Handbook of brain theory and neural networks, Cambridge, MA: MIT Press, 1995.

*This article concentrates on spatial learning and cognitive mapping.

7. Schmajuk, N.A., and Axelrad, E. Communication and consciousness: A neural network conjecture. Behavioural and Brain Sciences, 1995.
8. Schmajuk, N.A. The Psychology of Robots. Proceedings of the IEEE, Special Issue on Engineering Application of Artificial Neural Networks, E. Gelembi and J. Barhen (Eds).
*This article shows the connection between animal and robotic approaches to spatial learning and cognitive mapping.
9. Schmajuk, N.A., Lam, Y.W., and Gray, J.A. Latent inhibition: A neural network approach. Journal of Experimental Psychology: Animal Behavior Processes, in press.
10. Schmajuk, N.A., and Zanutto, B.S. Escape, avoidance, and imitation: A neural network approach. Adaptive Behavior, in press.
11. Schmajuk, N.A., and Buhusi, C. Occasion setting, stimulus configuration, and the hippocampus: A neural network approach. Behavioral Neuroscience, in press.

PAPERS SUBMITTED

12. Schmajuk, N.A., Lamoureux, J., William, P., and Holland, P. Occasion setting and stimulus configuration: A neural network approach. Psychological Review
13. Buhusi, C., and Schmajuk, N.A. Attention, configuration, and hippocampal function. Hippocampus.

PAPERS IN PREPARATION

13. Schmajuk, N.A., and Axelrad, E. Animal communication: A neural network approach.
14. Schmajuk, N.A. and Kasian, S.J. Landmark learning and spatial memory: A neural network approach.
*This article concentrates on spatial learning and cognitive mapping.
15. Schmajuk, N.A., Tye, J., and Gray, J.A. Latent inhibition and hippocampal function: A neural network approach.
16. Schmajuk, N.A. and Dragoi, V. Learning and evolution: A genetic algorithm approach
17. Schmajuk, N.A., Lamoreux, J., and Zanutto, B.S. Operant appetitive learning: A neural network approach
*This article studies different problems of spatial learning and cognitive mapping.

7. Interactions/Transitions

A. Communications to Scientific Meetings

1. Schmajuk, N.A. Stimulus configuration, classical conditioning, and spatial learning: Role of the hippocampus. Invited talk at the World Congress on Neural Networks. San Diego, June 4-9, 1994.
*This communication refers to hippocampal participation in spatial learning and cognitive mapping.
2. Schmajuk, N.A. Behavioral dynamics of escape and avoidance: a neural network approach. Simulation of Adaptive Behavior: From animals to animats. Brighton, England, August 8-12, 1994.
3. Schmajuk, N.A., Lamoureux, J., and Holland, P. Occasion setting and stimulus configuration: A neural network approach. Thirty-fifth Annual Meeting, The Psychonomic Society, St. Louis, Missouri, November 11-13, 1994.
4. Schmajuk, N.A., & Axelrad, E. Animal communication: A neural network approach. Meeting of the Eastern Psychological Society, Boston, MA, April 1995.
5. Schmajuk, N.A., Axelrad, E.T., & Zanutto, B.S. A neural network approach to animal communication. Society for the Quantitative Analysis of Behavior, Washington, D.C., May 26-27, 1995
6. Schmajuk, N.A., & Holland, P.C. Multiple response systems in classical conditioning. World Congress on Neural Networks, Washington, D.C., July 17-20, 1995.
7. Schmajuk, N.A. The psychology of robots. First Conference on Behaviorally Inspired Autonomous Systems. Duke University, March 5-6, 1996.
*This communication includes a section that refers to spatial learning and cognitive mapping.
8. Schmajuk, N.A., and Gray, J.A. The neurophysiology of latent inhibition: A neural network approach. Meeting of the British Experimental Psychology Society, York, United Kingdom, July 1996.
9. Schmajuk, N.A., Tye, J.N., and Gray, J.A. The neurophysiology of latent inhibition: A neural network approach. Abstracts of the Society of Neuroscience, 20, 1996.
10. Schmajuk, N.A., Lamoureux, J., and Holland, P. Multiple memory systems in classical conditioning: Occasion setting and stimulus configuration. 29th Annual Mathematical Psychology Meeting, Chapel Hill, NC, August 1-4, 1996.

B. Consultative advisory functions to other DoD laboratories

Dr. Christiane Duarte of the Naval Undersea Warfare Laboratory (US Navy) has been contacted and visited Duke in April 1996 to exchange information about spatial learning and

cognitive mapping in animals and robots. We wrote a joint proposal for MURI.

C. Knowledge resulting from our efforts is used.

See B above.

8. Inventions

None.

9. Honors/Awards

Duke International Award

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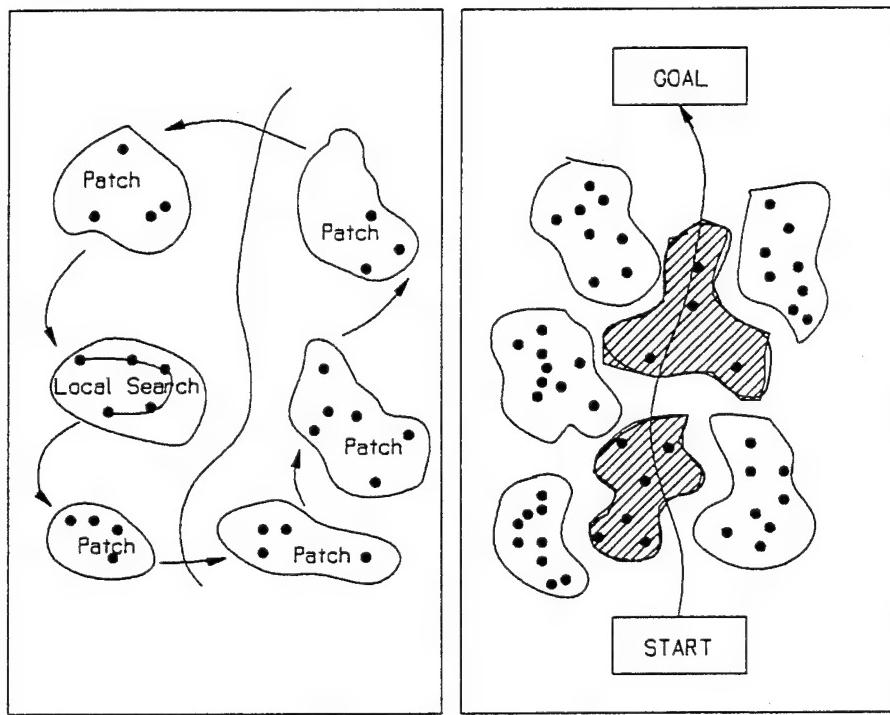


Figure 1. Left Panel: Spatial distribution of targets in the environment and movements within and between patches when all targets should be removed. **Right Panel:** Spatial distribution of targets in the environment and desired movement when the targets blocking the path between Start to Goal (lined patches) should be removed.

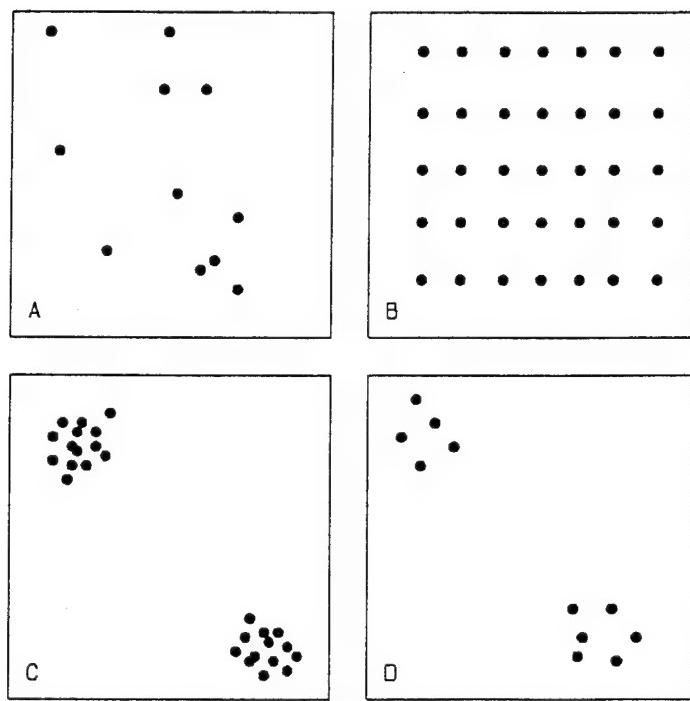


Figure 2. Spatial distribution of targets. (A) Random, (B) Uniform, (C) Concentrated patches, (d) Dispersed patches.

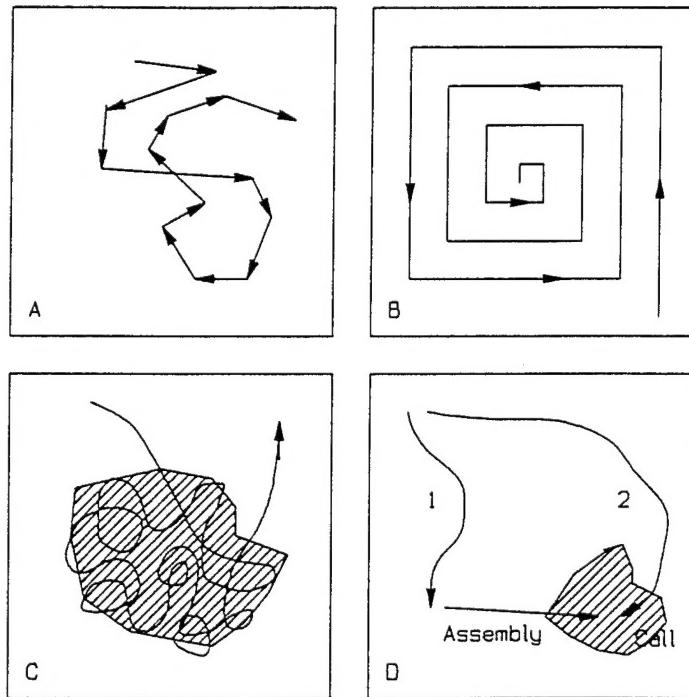


Figure 3. Search strategies. (A) Random walk, (B) Contracting square, (C) Patch-edge recognition, and (D) Social cooperation between Agents 1 and 2 when Agent 2 finds the target.

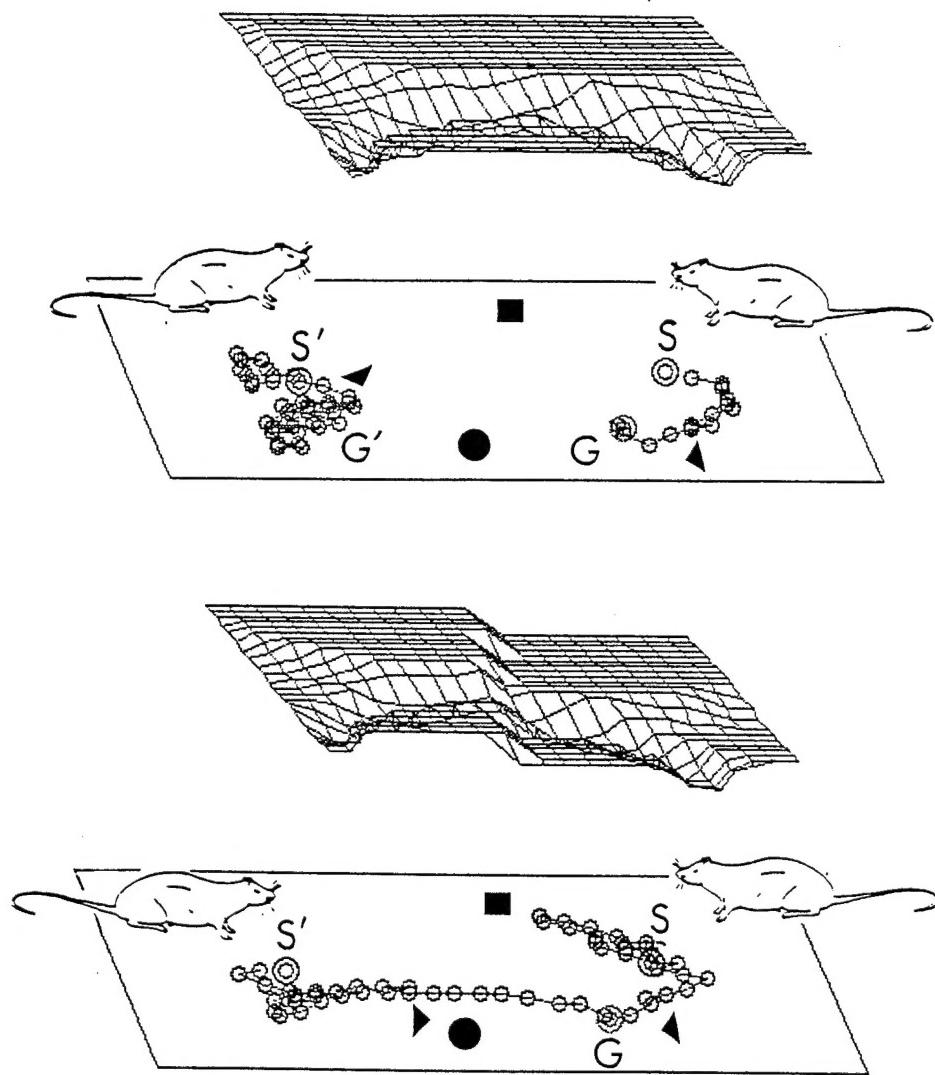


Figure 4. Place learning. Top panel: The location of the goal (G) is learned using only the visual angles to the square and round landmarks and, therefore, generalization surface A presents minima at G and G'. After training, when the rat starts at S it reaches G, when the rat starts at S' it reaches the mirror image of G, G'. Bottom Panel: The location of the goal (G) is learned using both the visual angles to the square and round landmarks and the visual angles between the landmarks and, therefore, generalization surface A presents only one minimum at G. After training, when the rat starts either at S or S' it always reaches G.

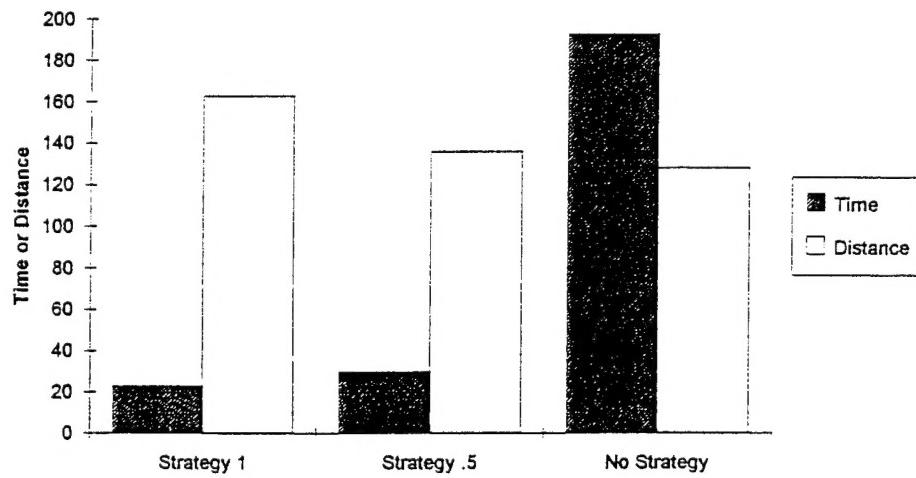


Figure 5. Search Strategies. Time to encounter 95% of the targets using a random walk with (A) constant speed, (B) decreasing speed with successive encounters and initial speed of 20 pixels/time unit, and (C) decreasing speed with successive encounters and initial speed of 10 pixels/time unit.

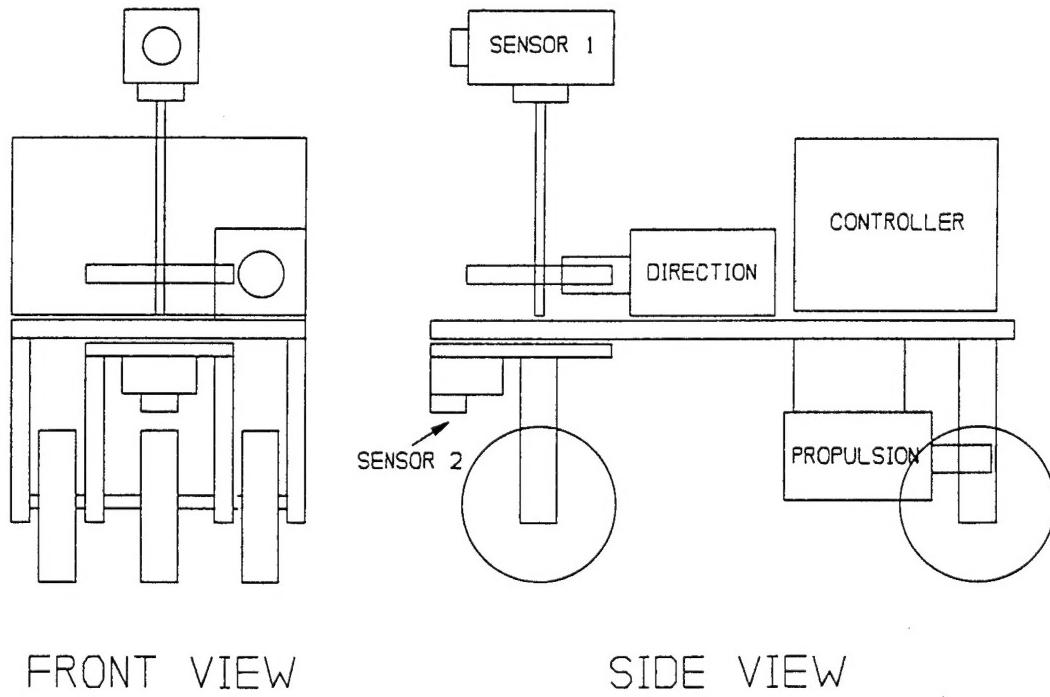


Figure 6. Experimental Robot. Diagram of the robot designed to perform searching behavior. Sensor 1 is an ultrasonic detector that senses the presence of walls in the direction of movement of the robot. Sensor 2 is a photoreceptor that senses the presence of active targets.